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Research Article

Incorporating variable lifetime and self-discharge into optimal sizing and technology selection of energy storage systems

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Abstract: Technology selection and sizing are key aspects of the design procedure for energy storage systems (ESSs) for power system applications. Here, the authors extended existing methodologies for optimal sizing and technology selection by introducing self-discharge effects, and variable ESS lifetime as a function of energy throughput, which results in a non-convex optimisation problem. Simulation results confirmed that making operational lifetime a variable has a significant impact on the results of the optimal sizing and technology selection problem. More specifically, considering the variable ESS lifetime as a function of energy throughput showed that ESSs of various technologies tend to operate such that their operational lifetimes would far exceed their calendar lifetimes. This has confirmed the importance of considering operational lifetime as a variable rather than a fixed value, as without doing this could result to underutilised and/or oversized systems. Taking into account, the self-discharge effect showed that the electrochemical technologies considered here, with the exception of supercapacitors, have low levels of self-discharge, which are largely obscured by the significant impact of the roundtrip efficiency characteristic.

Nomenclature

Sets and indices

N	set of energy storage (ES) technologies, indexed by n
I	set of demand profiles, indexed by i
J	set of energy price profiles, indexed by j
T	set of time intervals, indexed by t

Given parameters

$N_n^{\rm Cyc}$	cycle lifetime of ES technology n
$\overline{\rm SoC}_n, \underline{\rm SoC}_n$	maximum and minimum state of charge of ES technology n that ensures cycle lifetime $N_n^{\rm Cyc}$
Δt	time step
$\pi_j^{\rm E}(t)$	energy price profile
$P_i^{\rm D}(t)$	demand profile
$C_n^{\rm P}, C_n^{\rm E}$	investment costs for every MW and MWh of installed capacity
$\pi_{\rm VOLL}$	value of lost load
$k_n^{\rm SD}$	daily self-discharge ratio of ES technology n
η_n	roundtrip efficiency of ES technology n
$\bar{P}_{\rm G}^{\rm Export}, \bar{P}_{\rm G}^{\rm Import}$	export/import power line limits
$\underline{k}_n^{E/P}, \bar{k}_n^{E/P}$	minimum and maximum of energy to power ratio of ES technology n
$T_n^{\rm Cal}$	calendar lifetime of ES technology n

Estimated parameters

$F(i, j)$	frequency of occurrence of ith demand profile and jth energy price profile, (1)
$T_n^{\rm Op}$	operational lifetime of energy storage system (ESS) of technology n, (2)
$P_{\rm G}(t)$	imported/exported power to the grid, (4)
${\rm SoC}_n(t)$	state of charge of ESS of technology n at time t, (5)
$E_n^{\rm Opt}(i, j), P_n^{\rm Opt}(i, j)$	optimal energy and power capacities of ESS for ith demand profile and jth energy price profile, (14)
${\rm Profit}(i, j)$	profit of ESS that corresponds to optimal energy and power capacity for ith demand and jth energy price profiles, (15)
${\rm CAPEX}(i, j)$	capital expenditure of ESS, (16)
${\rm PLL}(i, j)$	penalty for the lost load, (17)
${\rm Rev}(i, j)$	revenue from energy arbitrage, (20)
$E_{\rm sc}(i, j), P_{\rm sc}(i, j)$	energy and power capacity scarcities to perform peak shaving, (18) and (19)
$T_{\rm sc}(i, j)$	duration of power scarcity, Fig. 3
$E_{\rm PS}, P_{\rm PS}$	energy and power required to provide peak shaving, Fig. 3

Optimisation problem variables

$P_n^{\rm ES}(t)$	scheduled power outputs of ES assets at time t
$\bar{E}_n^{\rm ES}$	rated energy capacity of ES assets
$\bar{P}_n^{\rm ES}$	rated power capacity of ES assets
$P_{\rm L}(t)$	scheduled load delivery

1 Introduction

Energy storage systems (ESSs) can fulfil a number of important functions within electricity transmission and distribution systems, including control of voltage and frequency; managing power flow constraints; and providing short-term capacity. ESS owners and operators can combine these functions – potentially in a synergistic manner – with financial benefits arising from fluctuations in energy price through arbitrage. Many methods exist to aid ESS developers in sizing and technology selection when planning a new project; however, these methods have a high computational cost, and do not account for particular lifetime constraints of the energy storage (ES) technology, which can fundamentally alter both the choice of size and technology of the asset installed, and how the asset is operated.

The research in this paper connects work from across three, usually distinct, categories within the literature: ESS scheduling and operation [1–7], ESS sizing [8–19], and ESS technology selection [19–21]. Bridging the divide between these areas is vital to enable the contributions of this paper, because the lifetime constraints depend on the size, technology, and operating regime of the ESS.

1.1 ESS scheduling and operation

ESSs have more complex operational requirements than conventional network assets due to their limited energy capacity; if energy needs to be exported or absorbed, then the necessary energy or headroom (storage capacity in which the absorbed energy can be stored) has to be available. These constraints have necessitated the development of scheduling and operational algorithms, which can manage the limited resources of the ESS to maximise its value over its lifetime. Many of the challenges in scheduling and operational planning arise from the difficulties of uncertain requirements [3–5], and from the combination of multiple storage, and potentially non-storage, assets to solve a given problem [2, 5]. In some cases, the uncertainty is not incorporated into the solution, thereby reducing the complexity of the required solution [1].

1.2 ESS sizing

Within the literature on ESS sizing, a variety of techniques are proposed, including linear search optimisation algorithms [9, 11], gradient-based algorithms [12, 19], stochastic optimisation algorithms [13, 17, 18], or heuristic techniques [8]. In recent ESS sizing studies [8–15], authors use models of ESSs that take into account roundtrip efficiency, energy throughput, calendar, and cycle lifetime. However, in practice, and for a variety of reasons including economic, efficiency, and reliability considerations, manufacturers offer ES modules with a limited range of energy to power ratios and charge and discharge rates. This poses additional constraints on sizing and technology selection [17–19].

In the studies referenced, specific sets of critical inputs to the optimisation problem are considered, such as load/generation profiles and energy prices. In general, authors extrapolate historical data without performing any sufficient analysis into the frequency of occurrence of specific events within the data [8, 9, 16]. This can lead to an overly complex sizing problem, with unnecessary analysis of similar scenarios in which the ESS is required to take no action, and which therefore have no bearing on the sizing problem. In other cases, the authors represent the required performance of the ESS using either single demand scenario or a small number of representative demand and price data, rather than investigating a broad state-space of plausible operational scenarios [17–19].

1.3 ESS technology selection

As the number of technologies available to ESS developers has increased, there has been an increased interest in algorithms to inform the selection of the most appropriate technology for a given application. Pham and Månsson in [22] suggested a fuzzy logic approach in order to perform multi-criteria analysis of different ES technologies for various applications. Miranda *et al.* [21] apply a linear search and consequent simulation method for sizing and technology selection. The methods are aimed to find single technology for the single application; however, it is shown in [2, 16] that combination of ES technologies can be more economically viable, and by Greenwood *et al.* [7] that there are cases in which provision of multiple services by a single ES asset can increase its profitability.

1.4 Original contributions of the paper

Sizing, technology selection, and operation and scheduling are all crucial areas of study for ESS. However, if they are considered separately, key factors cannot be fully accounted for: an example of this is operational lifetime, which depends on all three of these aspects. In this paper, the sizing and technology selection are combined with operational analysis to enable the incorporation of ESS lifetime constraints, dictated by lifetime energy throughput, into the problem formulation.

There are two main original contributions of the paper. Firstly, a typical approach in the literature has been to assume a fixed operational lifetime of ESS of between 10 and 15 years. However, as operational lifetime of ESS is in practice not fixed but depends on how ESS is operated, the lifetime was assumed to be a variable that depends on energy throughput, i.e. the outcome of the optimisation problem. The simulation results have confirmed that making operational lifetime a variable makes a significant difference to the results. The second modification was that a self-discharge effect of ESS was included. The resulting optimisation problem is smooth and non-convex and has been solved using an interior-point optimisation method in conjunction with the GlobalSearch MATLAB function ensuring global optimum.

The methodology has been tested on a range of scenarios that utilised frequency of occurrence based on historical data of particular characteristics of demand and price profiles to define the optimal size and ES technologies for a planning horizon equal to the expected lifetime of the ESS. A scenario-based state-space reduction method allowed reducing the number of future scenarios, while considering the required number of representative demand and energy price profiles. The frequency of occurrence calculations were carried out based on historical demand and energy price data, which allowed the evaluation of expected profitability within the optimisation problem solutions for the expected lifetime duration of the ESS.

Considering variable lifetime of an ESS as a function of energy throughput showed that, for the given case study network and data, ESSs of various technologies tend to operate such that their operational lifetimes would far exceed their calendar lifetimes; this has confirmed the importance of considering operational lifetime as a variable rather than a fixed value. Considering both operational and calendar lifetime during the sizing and operational scheduling processes enables the full utilisation of the operational capabilities of the ESS within the calendar lifetime.

2 Case study

This section provides a particular case-study network that includes an ESS comprising a combination of ES technologies, the ES characteristics that have been taken into account in the computations, and discussion of the historical demand and energy price data used in the analysis.

2.1 Distribution network

The network considered is shown in Fig. 1. Two overhead lines connect a substation to a grid supply point. Outgoing feeders are consolidated to one aggregated load. The power lines from the grid supply point are considered perfectly reliable and have a limited combined rating of 35 MW, which should not be exceeded. The ESS is located at the substation site and connected via a step-up transformer. Owing to its connection at the primary substation level, the ESS can provide additional network capacity.

2.2 ES characteristics

The proposed methodology, described in Section 3, has been applied for to selection the optimal combination of six different electrochemical ES technologies. However, the method is not ES

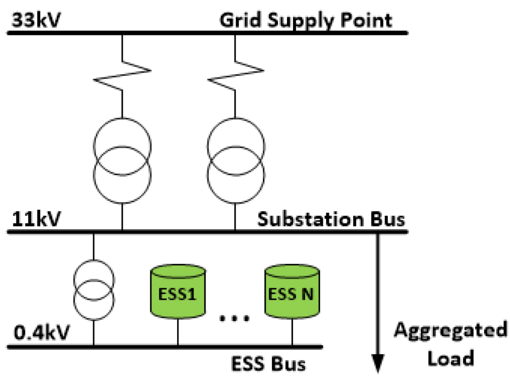

Fig. 1 *Case study network*

Table 1 ES technology parameters for optimal sizing and technology selection

N	Technology	Roundtrip efficiency, %	Cycle lifetime, cycles	Calendar lifetime, years	Self-discharge rate, %/day	Energy capacity cost, £/kWh	Power capacity cost, £/kW	Energy to power ratio
1	Li-ion	95	5000	15	0.2	490	325	0.1–6
2	ZnBr	70	3000	15	0	320	320	2–8
3	VRFB	70	10,000	15	0	490	325	4–15
4	NaS	75	4500	15	0	285	285	6–7.2
5	lead–acid	85	1500	10	0.2	260	320	0.25–6
6	SC	90	1,000,000	10	10	8100	175	0.005–0.025

type-specific, and any technologies for which data are available could be included. The technology characteristics used within the analyses are presented in Table 1.

2.3 Demand data

Power consumption data were taken from Customer-Led Network Revolution project [23]. A total of 365 days of historical demand data with a resolution of 10 min was used for this study. The data were averaged to 1 h intervals in order to comply with the time step used in the optimisation problem.

2.4 Energy price data

Energy price data were taken from Nord Pool Spot for the same year as demand [24]. Day-ahead auction prices represent the result of UK N2EX's day-ahead implicit auction market. The 365 days of historical energy price data, with 1 h resolution, were used for this study.

3 Methodology

This section describes the methodology for sizing and technology selection of ESSs. Selection of size and technology depend on many factors, including technology parameters such as efficiency, self-discharge, operational lifetime, and calendar lifetime; and wider system characteristics including network topology, demand, and energy price. In order to account for all of the above, a four-step algorithm has been developed, as illustrated in Fig. 2. The four steps are as follows:

i. create representative demand and energy price profiles;
ii. enumerate the frequency of occurrence for each scenario (combination of demand and energy price profiles);
iii. calculate the optimal size and technology for each scenario;
iv. evaluate profitability of the results.

3.1 Scenario creation

ESS sizing and technology selection should be informed by predicted future operating regimes; in this case, the applications are dependent on electricity demand at a local substation, and electricity price throughout the system. In this paper, each scenario comprises a 24 h data set containing demand and energy price with 1 h resolution. An ESS has an expected calendar lifetime of 10–15 years for electrochemical devices such as batteries and supercapacitors, and 20+ years for electromechanical systems such as pumped hydro or compressed air. Demand and energy price scenarios need to cover the expected lifetime of the system. In the literature, most authors consider a maximum of five representative scenarios [17, 18] and in some cases, only a single scenario is used [19]. The analysis in this paper is based on 365 days of historical demand and price data, and considers a fixed growth for both over a horizon of 15 years, which corresponded to the highest calendar lifetime of the ES technologies considered within the analysis. For simplicity and for illustrative purposes, we assume expected annual growth in demand and energy price of 0.5 and 1%, respectively. However, the proposed method does not exclude the use of more sophisticated demand and energy price behavioural models.

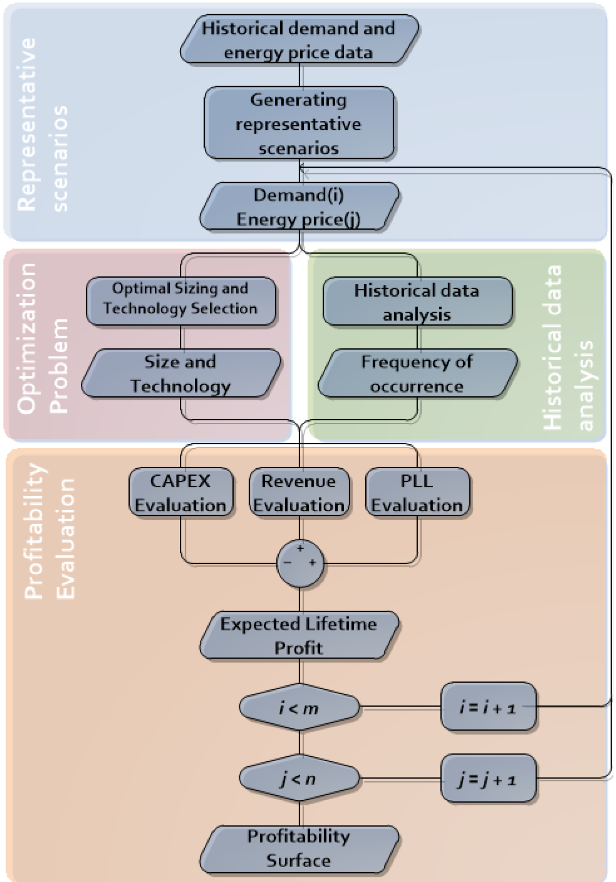

Fig. 2 *Algorithm for evaluating lifetime profitability*

To create the demand and price scenarios for analysis, ten profiles were extracted from each of the demand and price data sets, equally spread between the minimum and maximum value at each hourly time step. The result of this process is a combination of 10 demand profiles and 10 energy price profiles, therefore, a total of 100 scenarios. The approach taken here represents an effective compromise between accuracy and computational efficiency, given that the 5475 scenarios of demand and energy price profiles for 15 years ahead (365 days × 15 years) have been condensed into a computationally tractable scenario set.

It is important to emphasise that the scenarios created were necessary to create a representative data set in order to validate the proposed methodology. For practical applications, a more sophisticated methodology for scenario creation would have to be used; one that would take into account actual price, generation, and load correlations for the whole system. This is a separate subject which we do not address in this paper.

3.2 Frequency of occurrence

It is important to consider both the range of possible scenarios and their frequency of occurrence. Each demand and price scenario was compared to the historical data, and the number of days with the corresponding peak demand and energy price variation were enumerated. In order to normalise the result, the number of similar days was divided by the total number of samples (days) in historical data. The procedure was repeated for every combination of demand and energy price profiles, yielding a frequency of occurrence function for each combination of demand and energy price profiles (1)

$$F(i, j) = f(\mathrm{Demand}(i), \mathrm{Price}(j)) \tag{1}$$

3.3 Optimisation problem formulation

This subsection contains the mathematical formulation of the optimisation problem to carry out sizing and technology selection for a predefined installation site and a set of applications. That problem has been extensively researched in the literature discussed in Section 1; however, the authors have commonly assumed a fixed ESS lifetime between 10 and 15 years. However, ESS lifetime is not fixed; it is variable as it depends on how the ESS is operated, which is the outcome of the optimisation problem. Hence, the most important original contribution of the paper is that the proposed model of the ESS extends existing models used in sizing, siting, and technology selection papers [12, 17–19] by considering variable operational lifetime of ESS as a function of energy throughput, as shown in the below equation

$$T_n^{\mathrm{Op}} = \frac{2 \cdot \bar{E}_n^{\mathrm{ES}} \cdot N_n^{\mathrm{Cyc}} \cdot \left(\overline{\mathrm{SoC}_n} - \underline{\mathrm{SoC}_n}\right)}{\left(\sum_{t=1}^{T} \left|P_n^{\mathrm{ES}+}(t) + P_n^{\mathrm{ES}-}(t)\right|\right) \cdot \Delta t}, \tag{2}$$

where the numerator defines the total energy throughput of ES technology n and denominator defines the amount of energy that went through the battery during 24 h of operation. The quotient gives the number of days that ESS will be operating. Assuming that the ESS lifetime is a variable dependent on energy throughput makes the problem non-convex but, as shown in Section 4, this makes a very significant difference to the optimisation results.

The optimisation problem is formulated for six ES technologies simultaneously in a similar way to [19] using a 24 h time horizon and 1 h time steps. Twenty-four-hour demand and energy price profiles are given as input data to the optimisation problem. The resulting solution yields the optimal size and technologies of ESSs for a specific scenario of demand and energy price profiles.

The objective function (3) is designed to find a trade-off between revenue from energy arbitrage, per diem investment costs in ESS, and avoided penalties for the lost load due to input line capacity limits

$$\begin{aligned} \min \sum_{t=1}^{T} & [-P_{\mathrm{G}}(t) \cdot \Delta t \cdot \pi_{\mathrm{E}}(t)] \\ & + \sum_{n=1}^{N} \frac{\bar{P}_n^{\mathrm{ES}} \cdot C_n^{\mathrm{P}} + \bar{E}_n^{\mathrm{ES}} \cdot C_n^{\mathrm{E}}}{T_n^{\mathrm{Op}}} \\ & + \sum_{t=1}^{T} [(P_{\mathrm{D}}(t) - P_{\mathrm{L}}(t)) \cdot \Delta t \cdot \pi_{\mathrm{VOLL}}], \end{aligned} \tag{3}$$

with respect to:

$$P_n^{\mathrm{ES}+}(t), P_n^{\mathrm{ES}-}(t), \bar{E}_n^{\mathrm{ES}}, \bar{P}_n^{\mathrm{ES}}, P_{\mathrm{L}}(t)$$

Here, we define the positive value of power as consumption and a negative value as a generation. Hence, the negative sign in the first term of the objective function implies that the ESS owner/operator pays for power $P_{\mathrm{G}}(t)$ when it imports energy from the grid and receives income for the energy that is exported. The second term of the objective function defines the per diem cost of the ESS, where C_n^{P} and C_n^{E} are investment costs for every megawatt and megawatt hour of installed capacity, respectively. The third term defines the penalty for lost load, where $P_{\mathrm{D}}(t)$ is input data of a demand profile and π_{VOLL} the value of lost load (VOLL) (in GB, VOLL is approximately £16,940/MWh) [25].

The constraints of the optimisation problem are formulated in (2) and (4)–(13). Power balance at the node where the ESS is connected are satisfied by the below equality

$$P_{\mathrm{G}}(t) + P_{\mathrm{L}}(t) + \sum_{n=1}^{N} P_n^{\mathrm{ES}+}(t) + \sum_{n=1}^{N} P_n^{\mathrm{ES}-}(t) = 0. \tag{4}$$

The ES state of charge (SoC) level $\mathrm{SoC}_n(t)$ is defined by the below equation

$$\begin{aligned} \mathrm{SoC}_n(t+1) = {} & \mathrm{SoC}_n(t) \cdot \left(1 - k_n^{\mathrm{SD}} \cdot \frac{\Delta t}{T}\right) \\ & + \frac{P_n^{\mathrm{ES}+}(t) \cdot \eta_n + P_n^{\mathrm{ES}-}(t) \cdot (1/\eta_n)}{\bar{E}_n^{\mathrm{ES}}}. \end{aligned} \tag{5}$$

The second contribution of this paper is the inclusion of a self-discharge effect within the ESS model. The first term of (5) accounts for hourly self-discharge of the ESS, where k_n^{SD} is daily self-discharge ration of ES technology n. Since the self-discharge ratio describes relative value of the energy lost from the ESS during some period, $\mathrm{SoC}_n(t)$ has to be in relative units as well.

In order to ensure that the ESS is not charged and discharged concurrently, an additional equality constraint is applied

$$P_n^{\mathrm{ES}+}(t) \cdot P_n^{\mathrm{ES}-}(t) = 0. \tag{6}$$

The minimum and maximum SoC that can be reached is limited by inequality

$$\underline{\mathrm{SoC}_n} \le \mathrm{SoC}_n(t) \le \overline{\mathrm{SoC}_n}. \tag{7}$$

The net daily energy change is set to zero

$$\mathrm{SoC}_n(1) = \mathrm{SoC}_n(T+1). \tag{8}$$

The power output of the ESS n to meet power rating of the ES assets is limited by

$$0 \le P_n^{\mathrm{ES}+}(t) \le \bar{P}_n^{\mathrm{ES}}, \tag{9}$$

$$-\bar{P}_n^{\mathrm{ES}} \le P_n^{\mathrm{ES}-}(t) \le 0. \tag{10}$$

The input line capacity is included within the model as a constraint

$$-\bar{P}_{\mathrm{G}}^{\mathrm{Export}} \le P_{\mathrm{G}}(t) \le \bar{P}_{\mathrm{G}}^{\mathrm{Import}}. \tag{11}$$

Each ES technology has a power to energy ratio between a given maximum and minimum value. This constraint is expressed as

$$\underline{k}_n^{E/P} \le \frac{\bar{E}_n^{\mathrm{ES}}}{\bar{P}_n^{\mathrm{ES}}} \le \bar{k}_n^{E/P}, \tag{12}$$

where $\underline{k}_n^{E/P}, \bar{k}_n^{E/P}$ are the minimum and maximum values of the energy to power ratio of the ES technology n.

In order to ensure that the ESS operates no longer than its calendar lifetime, an additional inequality constraint is applied

$$T_n^{\mathrm{Op}} \le T_n^{\mathrm{Cal}}. \tag{13}$$

In theory, the optimisation problem needs to be solved for every combination of demand and energy price profiles, i.e. 100 times if we consider 10 demand and 10 energy price representative profiles. In such a manner, optimal energy and power capacities for each individual combination of demand and energy price profiles can be represented by

$$\text{Optimisation}[\text{Demand}(i), \text{Price}(j)] \rightarrow \begin{cases} E_n^{\text{Opt}}(i, j) \\ P_n^{\text{Opt}}(i, j) \end{cases} \tag{14}$$

However, in practice, for many scenarios, the ESS will not be required to take any action, so these scenarios can be excluded from the optimisation, further increasing the computational efficiency of this method. This exclusion is achieved by initially solving the problem for the most extreme case (highest energy price deviation and highest peak demand), and then moving sequentially to the lower demand and price-variate scenarios. Once a scenario is reached in which the ESS is not required to take action, the scenarios with a lower requirement can be excluded.

3.4 Profitability evaluation

The profitability is evaluated for every optimisation problem solution, which in its turn has been solved for every combination of representative demand and energy price profiles. The profit of a particular optimal solution is defined as a sum of capital expenses (CAPEX), penalty for the lost load (PLL), and revenue from energy arbitrage (Rev)

$$\text{Profit}(i, j) = \text{CAPEX}(i, j) + \text{PLL}(i, j) + \text{Rev}(i, j) \tag{15}$$

CAPEX is defined as a sum of investment costs for installation of energy and power capacities of each ES technology that has been included in the optimal solution. In the cases where the ESS was not required to operate, the PLL and Rev terms are set to zero

$$\text{CAPEX}(i, j) = \sum_{n=1}^{N} \left[E_n^{\text{Opt}}(i, j) \cdot C_n^{\text{E}} + P_n^{\text{Opt}}(i, j) \cdot C_n^{\text{P}} \right] \tag{16}$$

In the paper, peak shaving is considered as a product of energy arbitrage. If the demand is not met, a penalty is calculated for every megawatt hour of lost load. The penalty for the lost load of each individual optimal solution is calculated with respect to all representative demand profiles and the corresponding frequency of occurrence

$$\text{PLL}(i, j) = \sum_{i=1}^{I} \left[[E_{\text{sc}}(i, j) + P_{\text{sc}}(i, j) \cdot T_{\text{sc}}(i, j)] \cdot \sum_{j=1}^{J} F(i, j) \right] \cdot \pi_{\text{VOLL}}, \tag{17}$$

where $E_{\text{sc}}(i, j)$ and $P_{\text{sc}}(i, j)$ are energy and power capacity scarcities of the ith and jth optimal solution to perform peak shaving for the ith demand profile. $T_{\text{sc}}(i, j)$ is a corresponding duration of power scarcity. $E_{\text{sc}}(i, j)$ and $P_{\text{sc}}(i, j)$ are defined in (18) and (19), respectively. $T_{\text{sc}}(i, j)$ is defined graphically as shown in Fig. 3

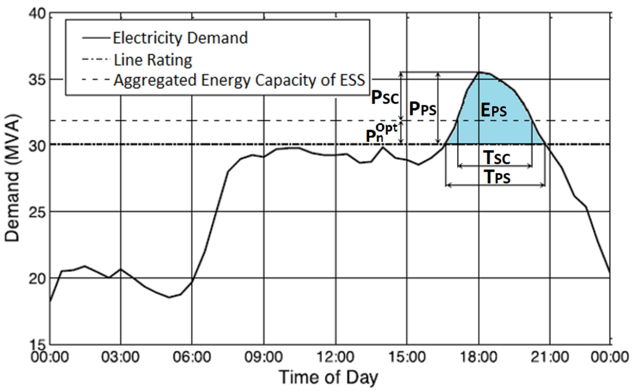

Fig. 3 *Peak shaving characteristics*

$$E_{\text{sc}}(i, j) = \begin{cases} 0, & E_n^{\text{Opt}}(i, j) > E_{\text{PS}}(i) \\ E_{\text{PS}}(i) - E_n^{\text{Opt}}(i, j), & \text{otherwise} \end{cases} \tag{18}$$

$$P_{\text{sc}}(i, j) = \begin{cases} 0, & P_n^{\text{Opt}}(i, j) > P_{\text{PS}}(i) \\ P_{\text{PS}}(i) - P_n^{\text{Opt}}(i, j), & \text{otherwise} \end{cases} \tag{19}$$

where E_{PS} and P_{PS} are minimum energy and power capacities required to perform peak shaving for the ith demand scenario (Fig. 3).

The total expected revenue of each individual optimal solution is found as a sum of revenues for each representative scenario of demand and energy price, and the corresponding frequency of occurrence

$$\text{Rev}_{\Sigma}(i, j) = \sum_{i^*=1}^{I^*} \sum_{j^*=1}^{J^*} \text{Rev}(i^*, j^*) \cdot F(i, j) \tag{20}$$

In its turn, revenue for each representative scenario corresponds to the optimal scheduling of the ESS and can be found by means of solving an optimisation problem similar to that described in the previous subsection, but for fixed energy and power capacities, as shown in the below equation

$$\min \sum_{t=1}^{T} [-P_{\text{G}}(t) \cdot \Delta t \cdot \pi_{\text{E}}(t)] \tag{21}$$

with respect to:

$$P_n^{\text{ES}+}(t), P_n^{\text{ES}-}(t) \tag{22}$$

subject to

$$\text{Equations (2), (4)} - (13)$$

where the rated power and energy capacities of the ESS are replaced by the optimal ones (23), (24) obtained through (14). Furthermore, it is assumed that the entire demand is met through (25)

$$\bar{E}_n^{\text{ES}} = E_n^{\text{Opt}}(i, j) \tag{23}$$

$$\bar{P}_n^{\text{ES}} = P_n^{\text{Opt}}(i, j) \tag{24}$$

$$P_{\text{L}}(t) = P_{\text{D}}(t) \tag{25}$$

3.5 Optimisation problem analysis and solver selection

Owing to the inclusion of the variable operational lifetime and self-discharge effect, the optimisation problems from Sections 3.3. and 3.4 are smooth and non-convex. If we consider six ES assets, as in the example in Section 4, the optimisation problem for 1 day scenario would contain 204 variables and 516 equality and inequality constraints. The problem can, therefore, be solved by means of an interior-point algorithm which is robust in solving convex optimisation problems [26]. To ensure that the solution is global, a GlobalSearch MATLAB function is employed. The GlobalSearch function implement the algorithm presented in Fig. 4.

The algorithm carries out a scatter search to generate a set of starting points for a non-convex optimisation problem, creating a set of convex subproblems [27]. For a more detailed description of the algorithm, the reader is advised to read Ugray *et al.* [28].

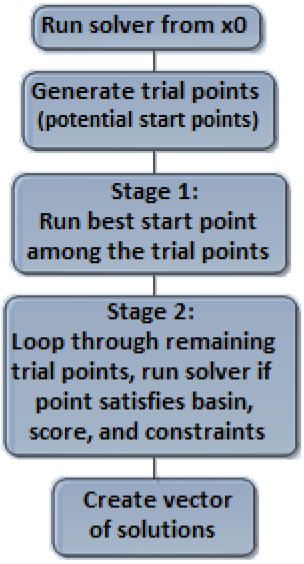

Fig. 4 *Global search algorithm [27]*

4 Results and discussion

4.1 Representative scenarios

The method described in Section 3.1 was used to extract a set of ten representative profiles of demand and energy price from the historical data. Figs. 5*a* and *b* illustrate these profiles of demand and energy price, respectively, covering a future 15 years. Annual growth of 0.5% was considered for demand and 1% for energy price. The highest numbered profile, ten in this case, corresponds to the highest demand profile or energy price profile, characterised by the highest peak demand and energy price variation, respectively. The lowest indexed profiles correspond to the lowest demand profile or energy price profile, characterised by the lowest peak demand and energy price variation.

4.2 Frequency of occurrence of representative scenarios

As shown in Section 3.2, the frequency of occurrence has been obtained for every combination of the representative demand and energy price profiles shown in Fig. 5. These frequencies of occurrence are shown in Fig. 6. It can be noted that low energy prices are more likely to be observed when demand is low, and high prices when demand is high. However, the relationship between energy price and demand is not straightforward and in reality would be dictated by the actual energy market conditions, considering the operation of the whole system. It can also be noted that Fig. 6 contains dark blue equal to zero areas, which correspond to zero frequency of occurrence. This means that high prices are unlikely to be observed when demand is low and vice versa. The proposed algorithm excludes these unlikely scenarios from the profitability evaluation, as the profit for these will be zero.

4.3 Optimisation problem solutions

The optimisation problem from Section 3.3 has been solved for every combination of representative demand and energy price profiles (Figs. 5*a* and *b*, respectively). By solving the optimisation problem for the highest energy price and highest peak demand profiles first, and moving sequentially to the lower demand and price-variate scenarios until reaching the front of scenarios where ESS is not required to take action, we reduced the number of optimisation runs to 52 instead of 100. Figs. 7*a* and *b* represent aggregated energy and power capacities combining all six ES technologies.

It can be noted that for the high demand scenarios (left-hand side), energy and power capacities keep constant to a certain value. This corresponds to the required amount of energy and power capacities to ensure minimum lost load when providing peak shaving. The high price scenarios (right-hand side) show much higher values of energy and power capacities. This is because, at

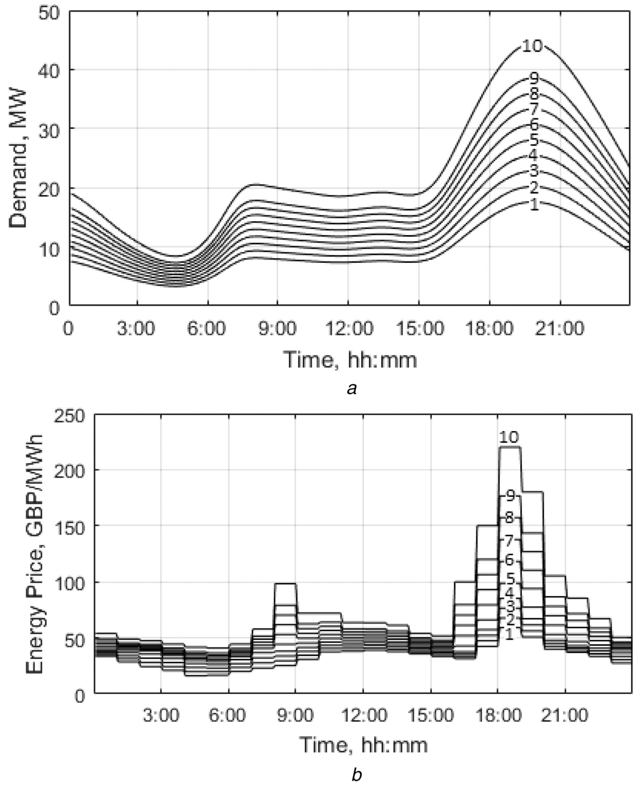

Fig. 5 *Representative profiles for 15 future years*
(a) Demand profile, ***(b)*** Energy price profile

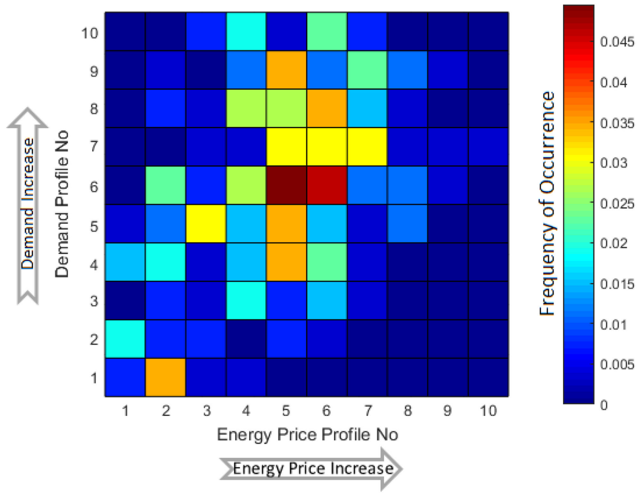

Fig. 6 *Frequency of occurrence of representative scenarios*

high price variation, energy arbitrage becomes profitable and the ESS stores energy from the grid during valley price period and releases it during peaks. In this case, energy and power capacities are limited by the local demand and reverse power flow limits. At the high demand and high price scenarios, ESS performs both peak shaving and energy arbitrage concurrently.

4.4 Profitability evaluation

According to the method described in Section 3.4, the profitability of each optimisation problem solution is calculated with respect to the corresponding aggregated values of energy and power capacities (Fig. 7), every combination of representative demand and energy price profiles (Fig. 5), and the corresponding frequency of occurrence of representative scenarios (Fig. 6). The resulting surface of profitability is presented in Fig. 8. The peak value of that surface corresponds to the most profitable configuration of ESS.

Thus, the optimal configuration of ESS corresponds to a power of 9.4 MW and an energy of 34.1 MWh, with expected profitability

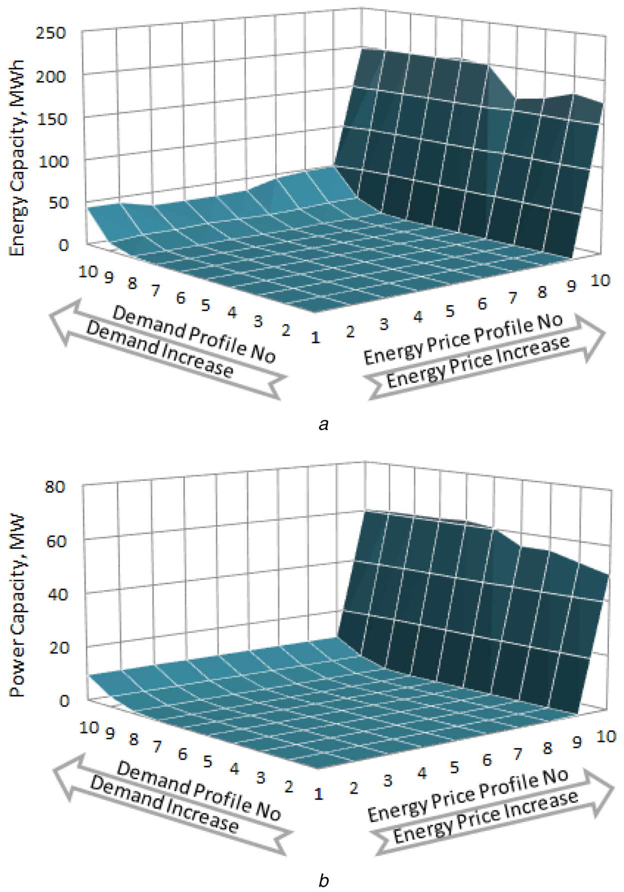

Fig. 7 *Aggregated optimal sizes of ESSs*
(a) Energy capacity, ***(b)*** Power capacity

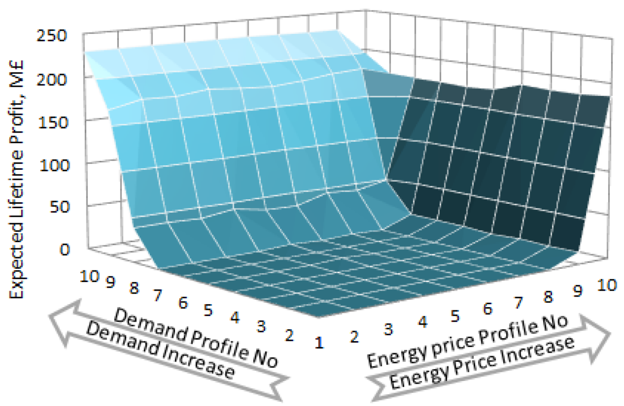

Fig. 8 *Profitability of solutions*

Table 2 Optimal configuration of ESS

Technology	*E*, MWh	*P*, MW	CAPEX, M£	Expected profit, M£
Li-ion	17.7	6.6	10.8	231.2
NaS	16.4	2.8	5.5	

of £231.2 M. The corresponding configuration is a hybrid energy storage system (HESS) consisting of Li-ion and NaS (sodium–sulphur) technologies. The results are presented in Table 2.

4.5 Parameters affecting ESS operation and lifetime

Besides optimal size and technology of ESS, the methodology used in this paper also enables more detailed study of the effects of various parameters on optimal operational lifetime. For that purpose, a series of optimisation runs were implemented.

Most of the manufacturers of ESS consider calendar lifetime expectancy from 10 to 15 years. In this paper, we calculate a separate indicator, operational lifetime, evaluated in (2). In this section, the optimisation problem from Section 3.3 was solved for the same case study and for various calendar lifetime limits, demand, and energy price scenarios.

The results of an average number of cycles and corresponding operational lifetime for different calendar lifetime limits are presented in Table 3. The results show that for the representative demand and price scenarios, optimal scheduling of ES assets without considering the relationship between calendar and operational lifetime could lead to underutilisation of the asset. Therefore, the inclusion of constraint (13) (calendar lifetime limits) to the optimisation problem ensures that the ES asset is operated in a way that fully utilises the asset such that its operational lifetime is less or equal to calendar lifetime.

4.6 Discussion

The example above illustrates the methodology for optimal sizing and technology selection of ESS for energy arbitrage that results in peak shaving. The results show that for the considered services, most of the profit comes from avoiding the penalties for lost load. If ESS was not installed, according to (17), the penalties would reach £240.7 M over 15 years. According to (20), allowing HESS to store cheap energy and release it at high prices, when peak shaving is not required, brings £5.4 M over the entire lifetime of HESS. According to Table 2, CAPEX is £16.3 M.

In the optimisation problem, it is assumed that the demand and energy price profiles are perfectly forecasted. To model a true behaviour of ESS, forecast uncertainties need to be taken into account. This can be done by reformulating the deterministic optimisation problem into stochastic problem considering several scenarios with corresponding probabilities at the same time. It has not been done due to complexity of the optimisation problem, which is characterised by non-convexity by the introduction of variable lifetime of ESS as a function energy throughput and self-discharge effect. The goal for future research is to overcome this problem.

The proposed approach is deterministic, given the underlying assumption that the frequency of occurrence of a particular combination of price and load profile in the future will be the same as in the past. Generally, it may be expected that the accuracy of the methodology will diminish with the planning horizon as the past may be a good indication of the future for the next few years but less so for 15 years ahead. This could be taken into account by applying weights that reflect reduced confidence in the optimisation results as the years progress. This is the subject of further research. If reliable long-term forecasts were available, the proposed methodology could be adjusted to reflect them.

Table 3 Optimal usage of ESSs for different values of calendar lifetime limits

Technology	No calendar lifetime limits		Calendar lifetime of 20 years		Calendar lifetime of 15 years		Calendar lifetime of 10 years	
	Cycles per day	Operational lifetime, years	Cycles per day	Operational lifetime, years	Cycles per day	Operational lifetime, years	Cycles per day	Operational lifetime, years
Li-ion	0.307	44.6	0.685	20	0.913	15	1	10
ZnBr	0.077	106.9	0.411	20	0.547	15	0.822	10
VRBF	0.911	30.1	1	20	1	15	1	10
NaS	0.389	31.1	0.617	20	0.822	15	1	10
lead–acid	0.063	65.4	0.205	20	0.274	15	0.411	10
SC	1	1367	1	20	1	15	1	10

The most computationally demanding stage in the methodology is optimisation. Intel® Core™ i7-4770 CPU with 3.4 GHz is able to solve the optimisation problem for 24 h scenario and six ES technologies within 10 min on average, but the method requires solving the problem numbers of time depending on the required resolution. The case study above required to solve optimisation problem 52 times, which took almost 9 h.

5 Conclusion

This paper has addressed optimal sizing and technology selection of ESS and proposed two important modifications of standard approaches proposed in the past. Firstly, as ESS lifetime is not fixed but depends on how the ESS is operated, the lifetime in this paper was assumed to be a variable that depends on energy throughput, which is taken into account within the optimisation problem. This results in a non-convex optimisation problem. The simulation results have confirmed that making operational lifetime a variable makes a significant difference to the design, planning, and operation of the ESS.

The second modification was that a self-discharge effect of ESS was included. The electrochemical ES technologies considered within the analysis, with the exception of supercapacitors, possess very small of self-discharge characteristics, which do not have a significant impact on the result, particularly when compared with the large effect from roundtrip efficiency.

The methodology has been tested on a representative set of scenarios. The frequency of occurrence, based on historical electricity price and demand data, was used to define the optimal size and ES technologies for a planning horizon equal to the calendar lifetime of the ESS. A scenario-based state-space reduction method allowed a tractable number of future scenarios to represent the complete data set.

Considering variable lifetime of ESS as a function of energy throughput showed that, for the given case study network and data, ESSs of various technologies tend to operate such that their operational lifetime far exceeds their calendar lifetime. Considering both operational and calendar lifetime during the sizing and operational scheduling processes enables the full utilisation of the operational capabilities of the ESS within its calendar lifetime.

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